GC 2012-5615: DEVELOPING A CROSS-CULTURAL MODEL OF PROBLEM SOLVING: COMPARING U.S. AND INDIAN ENGINEERING UNDERGRADUATES

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Developing a Cross-Cultural Model of Problem Solving: Comparing U.S. and Indian Engineering Undergraduates

The process of globalization has changed economies and the workplace worldwide. As this process has evolved, competitiveness has become a central issue. According to a typical metric of competitiveness used by government agencies and the media, which is the number of engineering graduates, the U.S. has been falling behind emerging economies, most particularly India and China.[1] However, in trying to decide who is winning and who is losing, Gereffi et al.[1] emphasize that it is important to consider quality as well as quantity. But what does "quality" mean in engineering, and how are we to measure it? These are the questions addressed in this paper within the topic of engineering problem solving.

A central topic for educators and researchers in engineering education and related fields is problem solving. A theoretically and practically rich collection of scholarly work surrounds this topic, from the perspectives of the learning sciences and engineering education. Within the discipline of cognitive psychology a theoretically-based distinction developed between "experts" and "novices" that was underpinned by hypotheses about learners' mental representations and how those mental representations changed both locally, during the solution of specific problems, and distally, as a natural developmental unfolding of skill due largely to extensive experience within a domain.[2,3,4,5] Engineering educators took a more didactic approach to the problem, recommending that certain problem-solving routines and practices be taught to students in order to develop disciplined and effective practitioners.[6,7,8]

The present study was motivated by a search for the best and brightest engineering undergraduates and the question of whether there were "experts" at this level. A classic body of research in cognitive psychology had suggested that undergraduate students are not capable of achieving levels of deep understanding in problem solving in their domain of study, i.e., in becoming experts.[9] In response to that research, other cognitive research questioned the very depiction of what it meant to have deep understanding.[10] One goal of this research was to re-test the original hypothesis[2,3,4,5] that deep understanding was beyond the scope of undergraduate learners. To test this hypothesis, students enrolled in introductory Mechanics at one of the best engineering institutes in India, the Indian Institute of Technology at Kharagpur (IIT-KGP), were tested using standard textbook problems. An Indian Institute of Technology was selected because of the reputation these schools have for providing world-class training. For comparison, the problem solving ability of the IIT-KGP students was compared to data from a U.S. research university, Texas Tech University (TTU), and to a less-renowned (compared to IIT-KGP) but well-regarded engineering institute in India, Manipal Institute of Technology (MIT). The experimental design provided a stringent test of the hypothesis that engineering undergraduates could achieve expert levels of performance because IITs recruited the very best students. The control conditions were appropriate because they provided some indication of normative performance within and outside India. A second goal was to implement an experimental methodology that was able to capture students' problem-solving behavior in sufficient detail to allow identification of prior knowledge and problem-solving strategies.

The next two sections present overviews of the classic position in cognitive research that asserts that undergraduates perform at a novice level and not at an expert level; and an alternative theory that suggests that the development of expertise is incremental with multiple intermediate states. These two positions will be tested in the present research.

Forward and Backward Inferencing Problem Solving Models

Problem solving requires cognitive strategies for retrieving, selecting, and applying knowledge. Research has shown that specific orders of equations in a solution are indicative of the level of understanding of the problem solver. In seminal studies in introductory physics mechanics, a domain with similarities to statics, two kinds of control were identified: backward inferences and forward inferences.[2,3,4,5] In applying **backward inferences**, the person begins with a variable value that is requested by the problem statement and identifies a principle that includes that variable. The selected equation may include other variables for which a value is unknown. The person then selects an equation involving that unknown variable or some other equation. He or she continues to select and apply equations until the desired variable value is found. Using the problem in Figure 1 as an example, an individual may choose to expand ΣF_X, which includes one of the desired variables (C_X), but also an additional unknown (T_X), so the individual must continue to search for equations before a variable value can be found. In applying **forward inferences**, the person selects equations that can be solved immediately. As a result, the solver can systematically add new information to his or her database until the variable values requested by the problem are found. Using the same example, choosing to solve for the ΣM_C allows one to immediately solve for tension (T), which is one of the variable values requested in the problem statement. Forward inferences have been associated with **expert problem solving**, and backward inferences have been associated with **novice problem solving**.[2,3,4,5] Other research, though, has found no differences in the application of forward and backward inferences in physics across a wide range of expertise.[10] Therefore, the available research is unclear about whether forward inferences are indicative of problem-solving expertise in undergraduate students.

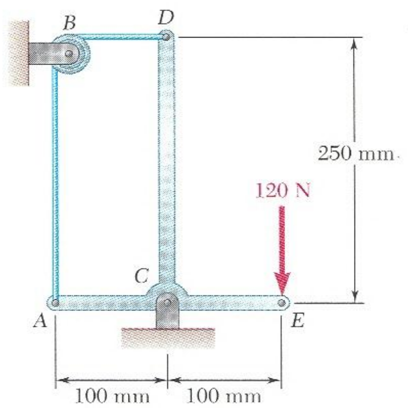

Figure 1. *Neglecting friction, determine the tension in* cable ABD *and the reaction at support* C.[12]

Learning Progressions

Learning progressions refer to a pedagogical construct that is associated with advances individuals make toward more sophisticated understanding in a domain. Learning progressions depict the acquisition of knowledge and skill as an incremental process through which competence is gained in a piecemeal manner. Intermediate levels of development can be useful stepping stones that represent productive but incomplete or partly incorrect systems of domain knowledge.[11]

According to theories of learning progressions, skill development is not inevitable and often depends in significant measure on instruction.[11] There are multiple paths in development, with specific pathways influenced by an individual's prior knowledge and experience, the nature of learning contexts and instructional supports, and specific learning tasks. The acquisition of knowledge and development of skills in a domain take place along multiple dimensions simultaneously. Knowledge and skill are interconnected in multiple and sometimes complex ways. Assessment requires fine-grained observations of individuals over time in order to identify critical bits of knowledge and the acquisition of successful strategies for effective problem solutions.

Case Study

Engineering educators have provided a number of useful didactic models for teaching problem solving,[6,7,8] but there are few cognitive models that show how mental processes change as students become skilled problem solvers in their area of training. The goal of this research was to assess expert thinking in undergraduates. One way to distinguish between expert and novice problem solvers is in terms of how they reason about a problem, particularly early in the solution. Expert solvers create an accurate and detailed mental model and use this to strategically select equations to solve the problem. Novice solvers follow a stereotypical algebraic approach.

Two models of problem-solving were evaluated here. According to a model of shallow forward inferencing, individuals select forward inferencing equations, but without demonstrating deeper understanding of the problem. According to a model of deep forward inferencing, individuals build a rich and accurate mental model of a problem prior to the application of forward-inferencing equations. The former model is consistent with the classic models of forward inferencing.[2,3,4,5] The latter model is more consistent with theories of learning progressions.[11]

To decide if deep forward inferencing took place in the present study, an explicit set of judgment criteria was necessary. A student was credited with deep forward inferencing if

- a Σ Forces or Σ Moment equation was selected that could immediately yield a value for a variable in the problem
- the Σ Forces or Σ Moment equation was the first equation that the participant produced
- the requisite assumptions or prior knowledge were correctly applied prior to solving the equation
- the equation was accurate
- the equation yielded a variable value.

Shallow forward inferencing was credited to the student if the student selected a Σ Forces or Σ Moment equation that could immediately yield a value for a variable in the problem (the first criterion above) but one or more of the other criteria was lacking.

The following predictions were made for this study:

- IIT-KGP students would show relatively strong evidence of deep forward inferencing
- deep forward inferencing is a sufficient, but not necessary, marker of problem solving ability
- deep forward inferencing would be associated with high ability, as reflected in cumulative grade-point averages (GPA).

The reasoning for these predictions is as follows. The first prediction was made because the stringent admission standards and intense engineering training programs at IITs suggested that these students were some of the most gifted engineering students in the world. The second prediction was made because of the possibility of successfully solving problems without using deep forward inferencing, that is, there are multiple ways of successfully solving a problem. The third prediction was made because the broad and rich conceptual knowledge required for successfully applying deep forward inferencing would plausibly be associated with general intellectual ability, as indicated by GPA.

Participants and Procedures

The participants in this study were 26 engineering students enrolled in Mechanics I at IIT-KGP (public-India). The comparison sample consisted of 23 engineering students enrolled in Mechanics I at MIT (private-India) and 28 engineering students enrolled in Mechanics I at TTU (public-U.S.).

Students participated about halfway through the semester and had covered the topics in the problems they were asked to solve. Students solved three problems. The results for Problems 1 and 2, shown in Figures 1 and 2, respectively, will be reported here. The third problem resulted in very low performance across all participants and will not be considered here. All participants met individually with an experimenter in a quiet room. They were instructed to solve the problems on paper as they normally would and to think out loud as they solved the problems. All sessions took approximately one hour. Problem solving was video recorded with the permission of participants. During data collection, the primary role of the experimenter was to prompt participants to continue to verbalize their thoughts if they fell silent for longer than a minute or two. At the conclusion of the meeting the U.S. students were compensated $25 for participation; the Indian students received a ballpoint pen, based on the advice of Indian faculty. All students appeared content with their compensation. Video recordings and paper solutions were used to analyze performance.

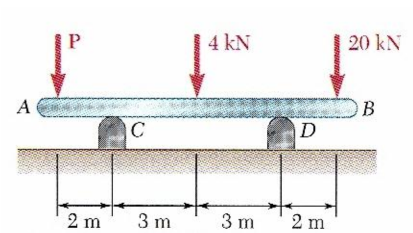

Figure 2. *The 10-m beam* AB *rests upon, but is not attached to, supports at* C *and* D. *Neglecting the weight of the beam, determine the range of values of* P *for which the beam will remain in equilibrium.*[12]

Results and Discussion

The findings (see Table 1) confirmed the first prediction that IIT-KGP students would demonstrate deep forward inferencing. This result contests the conclusion in the cognitive literature that undergraduates function at a novice, not an expert level of reasoning.[2,3,4,5,9] TTU students also showed evidence of deep forward inferencing, whereas MIT students did not. A statistical analysis of deep forward inferencing showed that the differences between schools were statistically reliable [$F(2,74) = 3.52$, $p = .03$]. Table 1 also shows that the shallow forward inferencing model did not distinguish between students, which was confirmed through a statistical test [$F(2,74) = 0.21$, $p = .81$].

Although the TTU students were more like the IIT-KGP students in their tendency to apply deep forward inferencing, they were more like MIT students in terms of overall problem accuracy. IIT-KGP students had overall significantly higher accuracy rates because there are multiple ways to reach a correct solution besides deep forward inferencing, which is consistent with the second prediction in this study.

Correlation analyses were conducted in order to test the third prediction that deep forward inferencing would be associated with high ability. The analyses showed a modest association between the application of deep forward inferencing and GPA ($r = .20$, $p = .08$), a non-significant association between the application of shallow forward inferencing and GPA ($r = -.08$, $p = .49$), and a strong association between overall problem accuracy and GPA ($r = .30$, $p = .008$). The overall pattern of correlations generally supports the third prediction.

Table 1. Percent Accuracy Across All Problem Solutions, Percent Application of Forward Inferencing Equations, Percent Application of Deep Forward Inferencing, and Mean Grade-Point Averages (GPA). (Percents adjusted for differences in GPA are in parentheses).

Institutions	Overall Problem Solution Accuracy	Application of Forward Inferencing Equations	Application of Deep Forward Inferencing	GPA (10-point scale)
IIT-KGP (PublicIndia)	65% (71%)	35% (31%)	23% (25%)	8.20
MIT (Private-India)	25% (29%)	30% (28%)	0% (1%)	8.35
TTU (Public-U.S.)	38% (30%)	39% (45%)	25% (22%)	9.29

In summary, the evidence for deep forward inferencing provides a “proof of concept” that contests the widely accepted claim that undergraduates cannot reason like experts. It also helps to establish an attainable benchmark for engineering curricula. Finally, it supports a model of deep forward inferencing, which is more consistent with learning-progression theory than with a shallow forward inferencing model.

Conclusions

The research presented here reveals both the outlines of a theory of expertise for engineering undergraduates and an empirical methodology for broadening and confirming the theory. The levels of performance across the data sets suggest several levels of skill. Some students are simply stumped by typical problems from the domain of study. There are conventional problem solvers who follow a fixed routine when solving problems. These students eventually reach the correct solution. There are incisive analysts who take time before attempting to solve a problem to reflect on the parameters and to develop a mental model. This reflective reasoning is evidenced in deep forward inferencing. Deep forward inferencing depends on prior knowledge, which plays a critical role in the problem solution and cannot be inferred from information given in the problem. The student must simply know this information. Similarly, knowledge of specific concepts, like *range of values* (e.g. Figure 2), and the ability to translate those concepts into mental models of the problem, are required to solve a problem. The student must be able to translate these concepts from a general form of knowledge to the requirements of specific problems.

The data from the present study begin to operationalize the cognitive construct of deep understanding as it applies to problem-solving in statics. In this respect, the study complements contemporary theoretical[13,14] and didactic[7,8] research efforts directed at advancing engineering education pedagogy. It is also consistent with learning-progressions theory, which by its nature combines theory[13,14] and instruction.[7,8] The primary contribution of this research is in establishing meaningful benchmarks and boundary conditions for instruction. It lays the groundwork for follow-up studies on how to promote the development of deep conceptual understanding and problem-solving skill.

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